Unified Transformer Based Generative AI for 3D Plant Image Modeling and Disease Detection in Smart Agriculture

INTRODUCTION

Sustainable agriculture is a vital element to guarantee the food security of the world, but it is endangered by the impacts of climate change and by resource limitation. Plant diseases are a major risk to agriculture, leading to considerable loss in yield and economy for farmers all over the world [1]. Conventional disease monitoring by manual visual inspection is highly subjective, laborious, and also tends to be too late to arrest an extensive disease breakout, which could result in the overuse of pesticide with low utilization.

There is a promising alternative in the development of precision agriculture through the application of Internet of Things (IoT) and Artificial Intelligence (AI). Rather than discriminative model-based approaches and hand-crafted features[2], deep learning models (CNNs, in particular) have achieved promising results for the provision of assistance to disease detection in 2D images in controlled conditions[3], but can be severely impacted, in field conditions, by fluctuations in light, shadows, or the perspective. It should be stressed that 2D images do not record the intricate 3D shape of the plant, and this shape is frequently required for an accurate diagnosis of diseases at early stages [4].

In this article we present a novel 3D based approach to overcome these shortcomings. We shall come up with a Generator Transformer Model that will be able to produce realistic 3D models of the plants based on the standard 2D-like photographs using low-resolution IoT sensors. Such a method removes the requirement of costly 3D-scan hardware. Then, information-rich 3D models will be analyzed by a strong (transformer-based) detection model to enable very precise disease detection and severity assessment [5].

This Research study targets region-specific crops in Maharashtra to develop a data-driven diagnostic system that leverages automation for real-time plant disease identification. The system is designed to enhance precision in intervention, minimize overuse of agrochemicals, and assist in

new practices towards the agricultural paradigm that society demands commanding to "Smart Farming, Healthy Eating, Long Living”

AIMS OF STUDY

To design and develop an AI framework that reconstructs 3D plant models from 2D images for accurate, Transformer-driven disease detection, supported by performance analysis for sustainable agriculture.

OBJECTIVES OF STUDY

1. To study and analyze the existing 2D plant images.
2. To create Unified Transformer Based system to generate 3D plant images from 2D plant images.
3. To develop an efficient 3D plant disease detection system using AI approach.
4. To evaluate 3D plant disease detection system in real time agricultural environment.

LITERATURE REVIEW

1. **IoT and Computer Vision in Agriculture:** In addition, the convergence of the Internet of Things (IoT) has resulted in large-scale automatic data acquisition in agriculture [6], where computer vision, particularly Convolutional Neural Networks (CNNs) are widely adopted for analysis. Benchmark studies have been carried out to demonstrate that CNNs can perform quite effectively in classifying plant diseases to high accuracy from massive 2D image databases under controlled environments [3][6]. Nonetheless, this is still a significant research gap because in practice these models are not robust in field operations conditions against cluttered backgrounds, changed lighting condition and occlusions. Most importantly, these methods are inherently limited as they treat only color and texture thus cannot encompass the geometric and morphological information inherent to a plant from its 3D information, which is pivotal for robust early detection [9].

2. **3D Image Synthesis and Generative Augmentation Model:** Success has been given to generative models, particularly Generative Adversarial Networks (GANs) [20], Denoising Diffusion Models, in the creation of high-quality synthetic data. In agriculture, their dominant use has been for 2D data augmentation - useful in creating new images of diseased plants to balance and enrich scarce datasets, which increases susceptance of classifiers [22]. The area of research that has been headed in the direction of 3D synthesis lately already posits to be interested in 3D synthesis in the current research frontier but the current techniques of 3D plant generation are costly and are limited with training data regarding the 3D scanners [24]. Based on this observation, we have a clear and significant research gap: the absence of a generative framework that can create 3D plant structures directly from the ubiquitous and cheap 2D images, a difficult problem which is addressed as 2D-to-3D lifting.

3. **Transfer to Transformer models in Agriculture:** Transformer, another representative of the powerful self-attention model that appeared in natural language, has proved to become a widely used mainstream in computer vision [27]. ViT: A pure-transformer model (ViT) has demonstrated being able to beat competing CNNs at image classification by (29) their success for the task of 2D plant disease classification. Importantly for this proposal, dedicated architectures such as Point cloud Transformer will be developed to apply directly to unstructured 3D point cloud data, which can be readily used to analyses the 3D plant models we visualize here and so unlock a more contextual and deeper understanding of disease expression than possible with 2D focusing methods [32].

Table 1 : Literature review on IoT, CNNs & Plant Phenotyping

Sr. No	Title, Year with Reference No.	Approach	Key Contribution	Limitations / Research Gap
1.	Using Deep Learning for Image-Based Plant Disease Detection. (2016) [6]	CNNs (AlexNet, GoogLeNet) on PlantVillage	Far-reaching study with 99 percent effectiveness on a free 2D dataset.	Its performance suffers in practical circumstances; it does not feature 3D context
2.	Plant disease identification from individual lesions and spots using deep learning. (2019) [7]	Explores individual lesions and spots	Challenged problems of field conditions of 2D models pointed out.	Identifies the importance of powerful approaches more than 2D analysis.
3.	Detection of apple lesions in orchards based on deep learning methods of cycleGAN and yolov3-dense (2019) [8]	Apple lesion detection system relied on YOLOV3.	CycleGAN can learn the features of one type of images & transplant them to other. This way disease dataset Increased.	Very sophisticated 2D system, yet still limited by the infamous limitations of 2D imagery.
4.	Plant disease detection and classification by deep learning. (2019) [9]	Survey of different deep learning in plant disease detection before their symptoms appears clearly.	Plain background images(mostly) Hyperspectral images (Before their Symptoms appear)	Reinforces the dominance of 2D CNNs and the absence of using 3D sophisticated AI models.

5.	A deep learning approach for the classification of rice leaf diseases (2020) [10].	CNN to classify rice disease	System distinguished healthy and diseased leaves from a set of 1500 rice leaves.	Diseased rice leaves with 78.44% accuracy.
6.	Cardamom Plant Disease Detection Approach Using EfficientNetV2[2022] [11]	U2-Net was used to remove the unwanted background of an input image by selecting multiscale features	Achieved a detection accuracy of 98.26%.	Concentrated on 2 diseases of cardamom plants Colletotrichum Blight & Phyllosticta Leaf Spot of cardamom
7.	Mobile app-based tomato disease identification with fine-tuned convolutional neural networks (2023) [12]	Transfer Learning to fine tune architecture (AlexNet, ResNet)	Over 95% accuracy is attained by all trained CNN models.	Self-collected data only contains images of tomato leaves from the North-Eastern part of India.
8.	Deep learning in image-based plant phenotyping. (2024) [13]	Plant phenotyping deep learning.	Survey of deep learning in measuring plant characteristics.	Features 3D phenotyping, although frequently makes use of multiple-camera installations or scanners.

9.	Internet of Things Assisted Plant Disease Detection and Crop Management Using Deep Learning for Sustainable Agriculture (2024)[14]	(APDDCM-SHODL approach) Automated Plant Disease Detection and Crop Management using Spotted Hyena Optimizer with Deep Learning.	It tested on fruit disease image (FDI) and leaf disease image (LID) dataset with 98.60% accuracy.	Only 250 samples each in the Fruit Disease Image (FDI) and Leaf Disease Image (LDI) datasets
10.	Fast and Accurate Identification of Kiwifruit Diseases Using a Lightweight Convolutional Neural Network Architecture. (2025) [15]	(AlexNet, VGG19, ResNet18, EfficientNet_B0 , MobileNet_V2) and optimizing algorithms	"Dataset distribution for kiwifruit, APPLE disease classification. kiwifruit disease dataset. (a) Bacterial canker; (b) Soft rot; (c) Health."	It covers two diseases (bacterial canker and soft rot) on Kiwifruit.
11	A Deep Learning and Social IoT Approach for Plants Disease Prediction Toward a Sustainable Agriculture [16]	SIoT paradigm, and the Lysis platform, the SIoT platform	Provide SIoT infrastructure and a responsive Web app that can predict when a plant would (or not) get a disease.	Small coffee leaf rust dataset
12.	Sustainable Agriculture Through IoT Based Plant	YOLO with the continuous	Enables real-time and remote crop observation	IoT-based image capture can be affected by lighting,

	Disease Identification and Crop Management Using Deep Learning.[17]	monitoring aspect of IoT.		weather, or positioning, which can degrade image quality and reduce detection accuracy.
13.	State-of-the-Art Deep Learning Algorithms for Internet of Things-Based Detection of Crop Pests and Diseases: A Comprehensive Review [18]	CNN architectures	Emphasizes reducing pesticide usage, improving precision agriculture, and promoting food security	As a review paper, it lacks novel datasets, algorithmic implementations
14.	AI Powered Plant Disease Detection and Diagnosis [19]	(CNNs), Random Forest classifiers, LIME and heat plots of attention	Achieves 96.16% accuracy, with reliable performance across cotton leaf diseases	The model was primarily tested on cotton leaf images

Table 2: Literature Review on Generative Models & 3D Synthesis

Sr. No	Title, Year with Reference No.	Approach	Key Contribution	Limitations / Research Gap
15.	A Review on Plant Disease Detection Using Hyperspectral Imaging (2023) [20]	UAV, Airplane based, satellite-based image platforms	Hyperspectral imaging is a nondestructive, fast, reliable technique	The price of hyperspectral cameras is very high, which limits the application for small-scale farmers
16.	Exploring 3D Transfer Learning CNN Models for Alzheimer's Disease Diagnosis from MRI Images (2023) [21]	ResNet, SE-ResNet, InceptionResNetV2	Achieve impressive accuracies: 94.04%(InceptionResNetV2) 92.68% (ResNet34) 74.15%(InceptionV3)	Only 160 images per class were used for training
17.	Optimal deep generative adversarial network and convolutional neural network for rice leaf disease prediction (2024) [22]	Generation Of Images of Leaf Diseases with Conditional GAN (cGAN).	Improved classification potential through an increase in 2D datasets.	Restricted to 2-dimensional image production.

18.	Denoising diffusion probabilistic models (2020) [23]	DDPM Noise-Conditioned Diffusion Probabilistic Models.	Brought in a novel family of strong generative models in high-quality image generation.	Still not generalized with use in 2D-to-3D synthesis in the agricultural field.
19.	Unsupervised learning of probably symmetric deformable 3d objects from images in the wild (2020) [24]	Novel view-synthesis using Autoencoder.	Created new two-dimensional perspectives of one picture.	Does not produce a consistent 3D model that can be analyzed downstream.
20.	Data augmentation using Generative Adversarial Networks (GANs) for GAN-based detection of Pneumonia and COVID-19 in chest X-ray images (2021) [25]	Covid-19 screening with Inception Augmentation-GAN.	Inception Augmentation GAN inspired by Data Augmentation.	Images have been collected from multiple sources and health centers with possibly different acquisition parameters and different scanner model.
21.	2D to 3D Image Conversion Algorithms [26]	CNNs, GANs, voxel-based networks, adversarial networks, and transfer learning	Presents comparison tables of Algorithms used, Datasets employed, Limitations and future directions	Review study only and does not provide any original experimental validation

Table 3 : Transformer-based Models

Sr. No.	Title, Year with Reference No.	Approach	Key Contribution	Limitations / Research Gap
22.	An image is worth 16x16 words: Transformers for image recognition at scale (2020) [27]	Vision Transformer (ViT	Large-scale pretraining (on datasets like JFT-300M and ImageNet-21k) allows ViT to match or outperform CNNs.	Needs mass pre-training; has not been applied to the three-dimensional synthetically derived agricultural data.
23.	Efficient identification and classification of apple leaf diseases using lightweight vision transformer (ViT) (2022) [28]	ViT in Apple Leaf Disease classification.	AppViT is combined feature of Convolution block and multi head attention.	Examined in a strictly 2D manner; not provided with the advantages of 3D structural analysis.
24.	Practical cucumber leaf disease recognition using improved Swin Transformer and small sample size. (2022) [29]	Swin Transformer to detect plant diseases.	Adopted a hierarchical transformer model that exhibited a very high measurement on 2D images.	Sharing the same limitation of other 2D methods; disregard the 3D geometry.
25.	Training data-efficient image transformers & distillation through attention. (2021) [30]	DeiT (Data-efficient Image Transformers).	Demonstrated the effective transformation of training of transformers on smaller datasets.	Discusses one of the main drawbacks of ViT, although it remains within the

				rubric of 2D image classification.
26.	Vision Transformer Architecture for Efficient Leaf Disease Detection(2024) [31]	A modified Vision Transformer (ViT)	High accuracies: Apple: 91.71%, Grape: 94.06%, Tomato: 91.83%, Potato: 92.99%	The ViT model includes over 36 million parameters, which may be unsuitable for deployment on resource-constrained devices (e.g., in rural or edge settings).
27.	Applications and perspectives of Generative Artificial Intelligence in agriculture (2025) [32]	GANs, VAEs, Transformers, and Stable Diffusion	Review of GenAI applications in agriculture, covering sectors such as precision farming, crop improvement, pest and disease management	Review-based; it does not propose or test a new model or experiment, which limits its novelty in technical contribution.
28.	Grape Disease Detection Using Transformer-Based Integration of Vision and Environmental Sensing [33]	Transformer-Based Lesion Detection Network	Ready for real-world application in vineyards.	Needs More Computational power

29.	PlantHealthNet: Transformer-Enhanced Hybrid Models for Disease Diagnosis and Severity Estimation in Agriculture [34]	Swin Transformer, Detection Transformer (DETR), and SAM2-UNet	This framework is trained for real-world farming with lighting, backgrounds, and large-scale fields' robustness.	High computation and latency due to sequential processing

In most of the literature, there is no integrated and low-cost pipeline that is capable of not only computing 3D structural data from a few 2D images available, but also able to utilize such enhanced data for a robust disease detection. Existing approaches are either constrained by the lack of information in 2D images or constrained by the expense of obtaining true 3D data. This study diffuses this gap by directly addressing and generating such 3D images from 2D images, which stands as a notable positive novelty proposed here. Moreover, the use of Transformers for processing this synthesized 3D data and integration of a cyclic self-improving feedback loop is a novel idea that has not been merged before in this setting.

RESEARCH HYPOTHESIS

Integrating Generator Transformer models for 2D-to-3D image synthesis will significantly improve the accuracy and robustness of plant disease detection across changing environmental conditions.

RESEARCH METHODOLOGY

Implementation will be performed in a systematic multi-phase manner ensuring establishment and integration of the components of the proposed novel framework.

- **Phase 1: Data Acquisition System**

  This first pass will be focused on data collection system. In this pass, High-resolution images of regional crops will be taken specific region of Maharashtra state. All images will be carefully annotated with the plant species, health state, name of the disease (if any) and level of severity (if any), generating a base dataset for the training and validation. This is in line with current smart farming according to which even field-level data collection is enabled by available technology [6].

- **Phase 2: Development of 2D-to-3D Generator transformer Model**

  To this end, a Generative Transformer Model will be developed and learn how to translate 2D-3D images as a part of this underpinning work. This architecture will borrow from recent state-of-the-art generative models such as GANs or Diffusion Models however with a Transformer backbone to better reason about global scene context [12]. They will train the model to predict the 2D appearance of the plant given some 3D form based on the 2D images. Output will be in the form of a 3D data augmented construct, such as a point cloud or voxel grid, as the rich three-round virtual twin of the physical plant.

- **Phase 3: Disease Detection Transformer-based Model**

  After the 3D data collection, a distinctive diagnostic model will be constructed. The type of model will be a Transformer-based one which is customized to the 3D information, e.g., a Point Transformer [14]. The 3D point cloud (synthesized in the previous step) will be the input to it, and it will be trained in two tasks: (i) the classification of the health of the plant and (ii) regression of a severity score that will depend on the spatial distribution and the area dimensions of the detected symptoms in the 3D plant model. More robust and accurate diagnosis will be achieved by employing the 3D data to perform diagnosis than using the 2D image only.

- **Phase 4: Iterative Working to gain more Precision**

  Some of the innovations we are proposing include a cyclic and self-improving operational loop. When a new 2D image is received, it first goes to the Generator Model which produces a 3D view that then is processed by the detection Model. The diagnostic reporting may be confirmed by an agroexpert. If the decision is wrong, feedback is used to adjust models of both the generator and detector, leading to an operation that learns and improves over time: like active learning framework. Additionally, the validated GM will be employed for data augmentation to adding a variety of common 3D training samples to enrich the detection of special rare diseases, and to improve multimodal diagnosis accuracy of the entire system.

EXPECTED OUTCOMES

1. Identification of gaps in 2D data for accurate disease detection and 3D reconstruction.
2. A working **Unified Transformer-based model** that successfully converts 2D plant images into high-resolution 3D structural representations.
3. Development of an AI-driven **3D disease detection system** capable of identifying disease presence, type, and severity.
4. Real-world validation of the system in agricultural settings.

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